Category

Data & AI

AI Data Readiness & Foundation Models Input Quality Playbook

Getting your data genuinely ready for AI, not just accessible to it

- Practitioner
- Intermediate
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- Administrator
- 10 April 2018
- 3 minute(s)

Overview

A framework for assessing and building AI data readiness — data quality, completeness, and structure appropriate for foundation model input — recognizing that AI model quality is fundamentally bounded by input data quality, and that data merely being accessible to an AI system isn't the same as being genuinely ready for it.

If data is technically accessible to an AI system, is it

effectively "AI-ready"? Technical accessibility isn't the same as genuine readiness — data quality, completeness, consistency, and structure all affect how reliably an AI system can use the data, and technically accessible but poor-quality data will produce poor AI output regardless of the model's sophistication.

What's the most common data readiness gap organizations discover

when starting serious AI initiatives? Inconsistent data definitions and quality across source systems that weren't apparent when the data was used for its original narrower purpose, but become significant limitations when aggregated as AI training or retrieval input.

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